State of Washington
Office of Insurance Commissioner

Mike Kreidler, Insurance Commissioner

A Report to the Legislature

Effect of Credit Scoring on Auto Insurance Underwriting and Pricing

Submitted By: The Office of Insurance Commissioner

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About the SESRC - Puget Sound Division

As part of Washington State University, the SESRC works to provide high quality social, economic, and behavioral science research services to the University and the State, with particular expertise in survey research methods and survey administration. SESRC's Puget Sound Division was established to improve the Center's capacity to meet research needs in Western Washington. Headquartered in Olympia, the Puget Sound Division has concentrated on expanding SESRC's provision of data analysis and information management.

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About PRR

PRR was founded in 1981 to provide clients with creative communications solutions. Our award-winning staff has directed thousands of research, marketing, media, community relations, and public policy programs. PRR prides itself on designing and conducting thorough research. Our capabilities include a variety of research methods, from which we select the best techniques for a project's purpose. Strategic application of these techniques coupled with our data analysis capabilities provides our clients with clear and concise answers to their questions. PRR's ability to engage our audiences contributes to high response rates and our skills and experience result in thorough, probing questions resulting in data for good decision-making.

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EXECUTIVE SUMMARY

In 2002 the Washington State Legislature passed ESHB 2544, restricting the use of credit scoring in personal lines of insurance underwriting. ESHB 2544 also directed the Insurance Commissioner to produce two studies, on the effects of credit scoring before and after ESHB 2544. To conduct the first study mandated by ESHB 2544, the Office of the Insurance Commissioner hired independent research and consulting services – PRR, Inc, and Washington State University's the Social and Economic Sciences Research Center, affiliated with Washington State University.

Three insurance companies each provided data on several thousand randomly chosen consumers. The insurance company data included

- age,
- gender,
- residential zip code,
- date policies started, and
- credit scores and/or rate classifications.

About 1,000 of each firm's consumers were contacted by phone. The phone survey gathered information about

- ethnicity,
- marital status,
- income level, and
- for 212 people whose policies had been cancelled because of low credit scores, information about how cancellation affected them, and how difficult it was to find replacement insurance.

Each of the three insurance companies used a different credit-scoring model. Only one insurance company had cancelled policies solely because of credit scores, and that practice had already been discontinued when the study began.

The purpose of the study was to find out whether credit scoring has unequal impacts on specific demographic groups – not to determine whether low credit scores correlate with higher loss ratios, or whether the use of credit scoring is inherently fair or unfair to individual consumers, or how accurate credit history information is.

This study has very specific limitations:

- Because practices vary widely from one insurance company to another, findings about credit scoring in one firm may not apply to others. Principal variations include:
  - The credit scoring model used;
  - The population to which it is applied, and

- The role of credit scoring in setting rates and assigning consumers to risk pools.

- Insurance companies vary in the way they set rates for people who do not have enough credit history to compute a credit score. Some companies view this as a negative factor, while others consider it a neutral factor.
- Certain ethnic groups in Washington have relatively few older people, making it difficult to compare them with other ethnic groups in the same age range.
- Washington has a low overall percentage of people of color, which limits the accuracy of the data for specific ethnic groups such as Native Americans.
- The study was based on records of insurance company customers, so it does not provide information about people who were refused insurance based on credit scores.
- This study does not examine whether the credit information used to set rates is accurate.

FINDINGS OF THE STUDY

The demographic patterns discerned by the study are:

1. Age is the most significant factor. In almost every analysis, older drivers have, on average, higher credit scores, lower credit-based rate assignments, and less likelihood of lacking a valid credit score.

2. Income is also a significant factor. Credit scores and premium costs improve as income rises. People in the lowest income categories – less than $20,000 per year and between $20,000 and $35,000 per year – often experienced higher premiums and lower credit scores. More people in lower income categories also lacked sufficient credit history to have a credit score.

3. Ethnicity was found to be significant in some cases, but because of differences among the three firms studied and the small number of ethnic minorities in the samples, the data are not broadly conclusive. In general, Asian/Pacific Islanders had credit scores more similar to whites than to other minorities. When other minority groups had significant differences from whites, the differences were in the direction of higher premiums. In the sample of cases where insurance was cancelled based on credit score, minorities who were not Asian/Pacific Islanders had greater difficulty finding replacement insurance, and were more likely to experience a lapse in insurance while they searched for a new policy.

4. The analysis also considered gender, marital status and location, but for these factors, significant unequal effects were far less frequent.

RECOMMENDATIONS

This study indicates that there is a need for examination of more companies and larger samples of consumers. Unequal effects are too common to be random events, but too varied across different insurers' situations for a clear pattern to emerge. Results vary too much from firm to firm to support a clear estimate of the overall size or pattern of unequal impacts on people of color, but the limited data studied do suggest that such impacts may exist. Data also indicate that low income people are more likely than higher income people to have their premiums raised as a result of credit scores.

Other aspects of credit scoring outside the scope of the data in this study – such as insurer refusals based on credit scores, and inaccuracy in credit scores – should also be investigated.

BACKGROUND

Since the mid-1990s, many insurance companies have been using consumer credit history as one of the factors they consider when they make decisions about how much to charge for auto, homeowners' and renters' insurance, and when to cancel or non-renew insurance policies.

Because credit scoring increases premiums for some people and reduces premiums for others, this practice has generated vigorous debate. Questions have been raised about the validity of credit history as a predictor of risk, its fundamental fairness, and the impact of credit scoring on people of color and the poor.

Insurance companies contend that there is a correlation between lower credit scores[1] and higher loss ratios. Therefore, insurers argue, using credit history is fair, and benefits consumers whose good credit scores indicate lower risks. Insurance companies also argue that using consumer credit history is non-discriminatory because it is "color blind," and because there is no consistent correlation between level of income and credit score.

Consumer groups contend, however, that while credit scoring may not be intentionally discriminatory against people of color and the poor, it may nonetheless produce disparate impacts that unjustly harm these groups. Consumer groups also note that the data in credit reports are often inaccurate, and that the process for correcting inaccuracies is cumbersome and time-consuming, especially for those whose time is already stretched by work and family obligations.

Moreover, credit scoring models and how they are used vary from one insurance company to another. Therefore, it can be very difficult for consumers to know how they are affected when credit scores are used as one element in a complex formula for determining rates or assigning consumers to risk pools.

Since 1996, insurers' use of credit scoring has increased, and so has the intensity of the debate about this practice. In 2002, 26 state legislatures considered bills to regulate or restrict this practice, and The Washington State Legislature adopted ESHB 2544. (Described in more detail below.)

In 2001, the National Association of Insurance Commissioners (NAIC) formed a work group to study this issue, to develop regulatory options, to provide consumer information, and to consult with the Federal Trade Commission (FTC) and the American Academy of Actuaries. Washington Insurance Commissioner Mike Kreidler co-chairs this work group.

The NAIC workgroup has already achieved two specific changes:

- The FTC has reiterated, in a strong public statement, that insurers must provide notice to consumers when an action, which is based on credit score, adversely affects them. Prior to this statement, insurers maintained that certain actions, such as not offering the lowest price, were not necessarily adverse actions.

- At the request of the NAIC, the American Academy of Actuaries has evaluated four studies on insurance credit scoring. They concluded that these studies do not directly address the issue of whether this practice has a disparate impact on people of color and/or the poor. This is significant because insurance companies have cited these studies as evidence that insurance credit scoring does *not* have a disparate impact.

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[1] Credit scores used in insurance are not the same as determinations of "credit worthiness" for mortgages, credit cards, or other loans. Credit scores are based on the same raw credit information used for those purposes. However, the various components of credit history are considered or "weighted" differently for insurance purposes than they are for credit worthiness. Which particular components of credit activity are considered, and the relative weighting of each component, depend upon which of many different statistical scoring models are used.

According to the Washington State Office of the Insurance Commissioner (OIC), consumers have submitted 374 written complaints involving credit issues between 1989 and 2003, and 82% of these complaints were received between 1997 and 2002. The OIC also reports 1,164 consumer phone calls about the use of credit scoring. In addition, the OIC has received numerous calls from concerned insurance agents about their inability to find insurance for people they believe to be good risks, but who have less than perfect credit scores.

The following accounts indicate why some Washington residents are concerned about the use of credit scoring in insurance:

- A Lacey couple was denied the best credit score because they pay all their credit cards in full each month.
- A Seattle man suffered injuries from an accident involving a drunk driver. After twelve surgeries and steep medical bills, he and his wife missed some payments on their bills. The wife is frustrated because she feels she shouldn't have to pay as much for their insurance as the person with the DUI.
- A Seattle area divorced mother sought bankruptcy protection when her ex-husband defaulted on his business debts and she was in danger of losing her home. Now, because of her ex-husband's actions, her credit score has plummeted and she is required to pay much more for her insurance.
- An American citizen established good credit in Canada, where he lived for 21 years. He recently moved to Washington and is having trouble finding reasonably priced auto insurance because insurers claim he has no credit history.
- A 50-year-old woman who has never had a traffic accident or a ticket was laid off from an Air Force installation where she had worked for 23 years. Her credit suffered because of her unemployment.
- A firefighter had to file bankruptcy during a dispute over his parents' estate because his brother was embezzling assets. Subsequently, he was not renewed by his insurance company because of his credit score.

ESHB 2544

In 2002, Insurance Commissioner Mike Kreidler, Attorney General Christine Gregoire, and Governor Gary Locke requested legislation restricting the use of credit scoring in personal lines of underwriting and rate-making.[2] In response to this request, the 2002 Washington State Legislature enacted ESHB 2544, now codified in RCW 48.18.545 (effective January 1, 2003) and 48.19.035 (effective June 30, 2003).

ESHB 2544 restricts the use of credit scoring in several ways:

1. Insurance companies may not cancel or non-renew a person's insurance solely because of his or her credit history;

2. Credit history may not be the principal basis for denial of insurance;

3. The calculation of credit scores may not include

[2] Personal lines of insurance include home, auto, and renter's insurance.

- the number of credit inquiries;
- medical bills;
- the initial purchase or financing of a vehicle or home;
- the type of credit, debit, or charge card;
- total available credit;
- disputed credit items (once resolved in the consumer's favor); and,
- lack of credit history, unless actuarial data show that the resulting rates are not excessive or discriminatory.

In September, 2002, the Insurance Commissioner issued rules to implement the new law. The rules define and further clarify the notices that must be provided to consumers when an adverse action is taken against them based on credit history. The rules also specifically direct insurers to file their credit scoring models with the Insurance Commissioner. Under the terms of ESHB 2544, these credit-scoring models are considered proprietary information that will be kept confidential unless the Insurance Commissioner undertakes an enforcement action.

ESHB 2544 also directs the Insurance Commissioner to produce two studies – the first due in January, 2003, and the second due a year later. The first study is a review and analysis of insurance credit scoring that includes:

1. The types of consumers who benefit from or are harmed by the use of credit history as a basis for insurance rating and underwriting;

2. The extent to which the use of credit scoring affects rates charged;

3. Whether insurance credit scoring results in discrimination against the poor or people of color.

This study focuses solely on auto insurance, and is designed primarily to address the third of these topics: effects upon the poor and people of color. In addition, it provides some information about the first topic – the general pattern of positive and negative effects from credit scoring.

The second report, due in January, 2004, will analyze how the implementation of ESHB 2544 has affected consumers.

METHODOLOGY

Credit reporting agencies, which are regulated by the Federal Fair Credit Reporting Act, sell credit-scoring services to insurance companies. These credit scores are used by insurers to decide whom to insure and how much premium to charge. A credit-scoring model takes personal credit history, and converts that data to a "credit score" using a complicated statistical formula.

These models are based on past patterns of credit behavior that have been correlated with insurance claims. Although credit-scoring models use the same raw data on which credit worthiness is determined for mortgages, credit cards, and other loans, they use it somewhat differently. The various components of credit history are considered or "weighted" differently for insurance purposes than they are for credit worthiness. The particular components of credit activity considered, and the relative weighting of each component, depend upon which of many different statistical scoring models is used.

This study collected empirical evidence on the demographics of credit scoring, and evaluated the incidence of credit scoring effects on certain demographic groups.

The data used in this study were based on records of policyholders who were insured by three insurance companies. Because of this reliance on customer records, this study cannot assess the impact of underwriting actions where individuals were denied coverage, nor of situations where an individual was quoted such a high price for coverage that they chose not to buy it from that insurer.

The statistical models used for computing credit scores are very complicated, and are considered proprietary assets by credit reporting agencies. Many variations of credit scoring models exist, and insurers often request that models be customized to fit their customer base, service area, and underwriting practices. Thus, there is no single credit-scoring model about which definitive conclusions can be reached. For examples of the factors used in credit scoring models see Appendix A. Different insurers use these factors in different ways in underwriting and pricing.

The primary focus of the analyses in this report was the relationship of negative effects to ethnicity or income characteristics. In both cases, analyses were done on an age-adjusted basis. Multivariate models also evaluated the possibility of effects by gender, marital status, and location.[3]

The results of this study begin to describe the range of possible results from credit scoring, but are directly applicable only to the three firms whose customer data was used.

None of these analyses could determine whether the shifts in costs (lower costs for people with higher credit scores; higher costs for those with lower or no credit scores) for a specific demographic group were correlated with higher risks or claims for that group. This study examines the question of *whether the cost shifting affected all demographic groups equally.*

DATA

Three insurance companies each provided data on several thousand randomly chosen consumers. Each of the three insurance companies used a different credit scoring model. Only one insurance company had cancelled policies solely because of credit scores, and that practice had already been discontinued when the study began.

[3] Two location distinctions were tested: Eastern Washington versus Western Washington, and inside a federal Metropolitan Statistical Area versus outside such areas. Federal Metropolitan Statistical Areas include counties with either major urban centers or significant suburban populations related to major urban centers.

The insurance company data included

- age,
- gender,
- residential zip code,
- date policies started, and
- credit scores and/or rate classifications.

About 1,000 of each firm's consumers were contacted by phone. The phone survey gathered information about

- ethnicity,
- marital status,
- income level, and
- for 212 people whose policies had been cancelled because of low credit scores, information about how cancellation affected them, and how difficult it was to find replacement insurance.

STATISTICAL METHODS

The primary statistical methods used were linear and logistic multivariate regressions. Linear regressions calculate the best statistical "fit" among factors when they have arithmetic relationships; for example, when one factor tends to rise whenever another falls. Linear regressions were used to estimate the relationship between demographic characteristics and numerical outcomes or measures, such as credit scores or discounts. Logistic regressions calculate the best statistical "fit" among factors that influence a probability. For example, the models estimate how much an increase in a particular factor changes the probability of an outcome event. Logistical regressions were used to estimate relationships when the outcome under study was a categorical yes/no, such as being placed with a higher cost pool, having no usable credit file, or having a policy cancelled.[4]

Multivariate regressions are used to simultaneously estimate the strength of multiple relationships among factors. For example, success in some sports may be a function of an athlete's physical characteristics, such as height and speed. Because longer legs cover more ground, the two often go together – but not always. Separately comparing performance by height and by speed will overestimate the effect of each. A multivariate approach produces a pair of simultaneous estimates for the separate contribution of each factor without "double counting" the same performance for someone who is both tall and fast.

Multivariate procedures are essential to this study because of the inter-relationship of age with income and ethnicity. Income generally rises with age, up until retirement age. In Washington State's population, many ethnic minorities have arrived in substantial numbers over the last few decades. As a result, there are relatively few older minority members in the population. If data are considered only by ethnicity, any

[4] In many cases, stepwise regression procedures were used. With stepwise regression, factors are added sequentially to the model. At each step, all of the statistically significant factors not yet included are tested for inclusion in the model equation. The factor which most improves the fit of the model is then added. This process is repeated and continues until all not-yet-included factors would not be statistically significant if added to the model. The standard probability value of .05 was used as the statistical significance criterion.

practice where older individuals have better results than younger ones can be misinterpreted as having a negative effect on minorities.

Because there is a substantial history in law and practice supporting higher risks and therefore higher premiums for younger drivers, age effects that favored older drivers were treated differently in this study from other demographic patterns. Analyses to detect other patterns were done on an "age-adjusted" basis so that age-related patterns were not mistakenly classified as unequal effects on groups based on income, race, gender, marital status or location.

Sample Size and Frequency of Response

The sampling frames for telephone surveying were developed from contact information for random samples of customers from each of the three firms. The first step was to use the services of Experian to check and update the telephone numbers for those in the lists. This step resulted in approximately 10% of the telephone numbers being updated.

The goal was to obtain a response rate of approximately 50%. Names were initially selected from the sample lists, and then five attempts to reach those telephone numbers were conducted on various days of the week and at various times of the day to control for sampling bias. Additional potential respondents were randomly selected from the sample lists only after five attempts without a successful interview, or when a disconnected or wrong number was determined to be non-traceable.

Non-Response to Specific Questions

Some of the survey respondents declined to answer specific demographic questions. In come cases, the respondent was not the policyholder and did not know some of the requested information. The following table indicates the "decline" and "don't know" percentages for the income question. Refusal and "don't know" rates on all the other items were substantially lower. These results are consistent with typical refusal rates for such demographic questions. In fact, the refusal rate for the income question was about half of what is normally experienced.

Figure 1
Percentage Who Answered Refused or Don't Know

	Firm 1		**Firm 2**	**Firm 3**
	Cancelled/High Score	General Sample		
Income	10.70%	7.5%%	8.80%	8.90%

Developing and Selecting Regression Models

Although the questions posed for this study appear clear and direct, answering them is complicated. Each insurer had different practices and provided different data. Company policies changed in important ways during period under study. The relationship between credit scores and factors such as income can take several different forms, [5] which expands analysis beyond a single test of a single variable. The results presented in this report

[5] Credit score might double when income doubles. Or, credit score might rise whenever income rises, but not at a constant rate. As an example, doubling a low income might be associated with a credit score increase of 50%, while doubling a middle income might be associated with a much smaller credit score increase, like 20%. Or very low-income individuals might have lower credit scores than middle and upper income individuals, among whom income makes no difference at all.

were selected after investigation of many alternatives as providing the most accurate and representative picture of the relationship between credit scoring and demographic characteristics in these samples.

STRENGTH OF THE RESULTS

The multivariate regression models only explain a fraction of the variance in score or discount found in the sample population. The strength of the relationship estimated in multivariate, models are measured using a statistic called R-squared. If there is no correlation, the R-squared would be 0. If the model combined several factors to produce an exact prediction of each policyholder's score or discount, the R-squared would be 1.0. R- squares for the regressions for this report range roughly from 0.04 to a 0.3, with most between .05 and 0.15. (See Appendices C through E) This indicates that while there are statistically detectable patterns in the demographics of credit scoring, most of the variation among individual scores is due to random chance or other factors not in this data.

Some of the correlations with specific factors are strong and consistent. In particular, there is a strong positive correlation with age: older individuals tend to have more positive credit scores and score-influenced insurance effects. Other correlations are not as strong, as noted in the discussion of individual analyses.

THE ANALYSIS

FIRM I

Questions

The first review involved three questions:

- Are credit scores independent of demographics?
- What were the effects of credit-based policy cancellations?
- What is the pattern of credit scores among this insurer's policyholders?

Structure

Policyholder information was provided which covered three periods, during which the company had three different policies on the use of credit scores.

1- Period One: For a time, the company was terminating coverage of some policyholders based on negative credit score information. A sample of policyholders cancelled during this period was provided.

2- Period Two: The company discontinued credit-based cancellations, but continued to acquire credit scores on all policyholders and applicants, using this information for risk and rate assignment. A random sample of all policyholders was provided for this period. In addition, a sample of very high credit score policyholders was provided for this period. This sample was used for comparison with the cancelled policyholders.

3- Period Three: The company shifted to using credit scores selectively, acquiring this information only on a fraction of new applicants. How these individuals were selected or how the information was used is not known. A small random sample of policyholders who were first covered during this period was included.

Cancelled and High Score Samples

The samples surveyed included cancelled policy holders (n = 212), as well as those with the highest credit scores (n= 217), providing a margin of error of approximately of +/- 5% for a yes/no question.[6] The response rates for those cancelled and for those with high scores were 66% and 71% (respectively), of those whom the interviewers tried to contact.

General Sample

The survey of the general sample of policyholders resulted in 996 responses. The response rate was 61% of those whom the interviewers tried to contact. This sample sizes provided a margin of error of approximately +/- 3 percent for a yes/no question.

Data Provided

In addition to age, gender, and zip code, the insurer also included credit scores and policy start dates.[7] Three separate samples were provided:

1- Policyholders previously cancelled because of low credit scores
2- Current policyholders with very high credit scores, and

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[6] This means that we can be 95% confident that the survey results for a typical yes/no question are within +/-5% of the results we would get if we surveyed the entire population. A confidence level of 95% means that only once in 20 times would we be wrong in making this assumption.

[7] As well as some driving record information that did not play a major role in this analysis.

3- A random sample of current policyholders.

Period 1

Demographics of Cancellation

To determine whether credit scores were independent of demographic characteristics, the sample of cancelled policyholders was compared with a sample of policyholders from the extreme high end of the credit score spectrum. Credit scores ranged over a scale of about 560 points. The threshold for policy cancellation included the bottom 0-150 points on that scale.[8] The sample of very highest credit scores were all within 20 points of the maximum, ranging from 540 to 560.

The dominating statistical difference was age. There was almost no overlap in the ages of the two groups. Ninety percent of the cancelled policyholders were under 55; in contrast, 93% of the highest scoring policyholders were over 65. Given this near-total separation of the two groups, there was very little potential to determine what other differences existed between the groups. [9]

These two samples were so different that we can conclude that credit scoring is definitely not totally independent of demographic characteristics. However, age differences so dominate this comparison that no definitive conclusions could be reached about possible demographic differences other than by age.

Survey Data on Cancellations in Period One

The phone survey asked cancelled policyholders additional questions about the consequences of cancellations. The key results were:

- Five percent of those cancelled could not obtain replacement coverage.
- Over a quarter experienced a period of no coverage between the expiration of the cancelled policy and obtaining a replacement policy. This had a particular (statistically significant) impact on minorities. Minority cancelled policyholders more often reported a period of lapse in insurance coverage between cancellation and obtaining new coverage. A substantial 54.3% among minorities reported a lapse in insurance coverage, compared to 24.2% of whites.
- Over 40% reported that obtaining replacement insurance was "very difficult." Higher premiums and applications to multiple insurers often resulted.
- Less than half reported that the letters they received from insurers adequately explained the reasons for cancellation.
- Over one quarter of those cancelled for low credit scores had no "incidents" in the insurer's records, though some had been with the insurer for more than ten years. Seventeen percent of apparently accident-free cancelled policyholders were minorities.

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[8] Some additional cases with higher credit scores were also coded as having been cancelled for credit score reasons, although their recorded credit score was above the cancellation cutoff indicated by the firm.

[9] To the very limited extent that the two samples overlapped, the cancelled policyholders included more minorities, more single/divorced/separated individuals, and more very low-income individuals. However, the dissimilarity of the samples makes these findings inconclusive.

Period Two

Period Two had the largest sample of any of the three policy periods covered in the data.

Credit Score

In Period Two, non-zero credit scores varied over a range of about 535 points.[10] Age was the dominant demographic factor associated with credit scores.[11] On an age-adjusted basis, there was no statistically significant relationship between credit scores and ethnicity or income.

Score of Zero

Inadequate credit files resulted in scores of zero, which presumably had a negative effect on rate classification. The only statistically significant association was that very low-income policyholders were much more likely to have insufficient credit history. Overall, only about one in 25 policyholders had a zero score, but for those in the lowest income group (less than $25,000 annual income), those probabilities shift to one in five.

Period Three

Credit scoring was only performed selectively, and the sample was too small to determine either the demographics of those selected for credit scoring or the patterns of their scores.

FIRM 2

Questions

Based on the findings from the first review, the principal questions were to determine the demographic pattern of both credit scores and the economic effects of those scores. Effects on policyholders with scores of "zero" due to inadequate credit history were identified as requiring separate analysis.

Structure

Firm 2's application of credit scoring was the simplest to analyze. Results for this firm have the fewest technical complications. This firm used credit scores to determine discount percentages from rates otherwise determined by traditional underwriting criteria, so the effect of credit scores is clearly represented by the distribution of discounts. The firm did not implement other major changes in rate setting at the time they implemented credit scoring. As a result, there is a substantial population of policyholders carried forward from the pre-credit scoring period.

This firm also had a significant number of policyholders with insufficient credit files. After discussion with the Office of the Insurance Commissioner when they filed their rating plan, the firm chose to rate such individuals at approximately the average discount given to all other customers. So, although we have separately analyzed the demographics associated with their "zero score" policyholders, it is not clear that having a "zero score" has a negative impact on those insured by this particular firm.

Sample

The survey resulted in 1,000 responses. Among those contacted, 72.6% agreed to participate. This constituted 43.3% of those whom the interviewers tried to contact. This sample sizes provided a margin of error of approximately +/- 3 percent for a yes/no question.

Data Provided

In addition to age, gender, and zip code, the insurer provided data on credit score, rate category, discount,

[10] This credit score scale did not start at 1, but at an arbitrary higher number.
[11] On average, every ten years of age was associated with an increase in credit scores of approximately 37 points (out of 535).

score order date, unusable thin or nonexistent credit record, and policy start date.[12]

Analyses

Premium[13]

Rate adjustments based on credit scores ranged from 17 % below average to 33% above average. Age was the more strongly correlated with credit-based rate adjustments than any other demographic factor considered.

Ethnicity

There were statistically significant differences, on an age-adjusted basis, for two ethnic groups, when compared with the majority ethnic group, Caucasians:

Credit scoring affected rates for two ethnic groups:[14]

- Rates for Asian/Pacific Island policyholders were reduced by about 5.5% of the average rate, relative to whites of similar age.
- Rates for Native Americans were higher by about 15.8% of the average rate, relative to whites of similar age.

Income

Credit scoring raised the average costs for poor policyholders relative to affluent policyholders. Across the entire income range, better-off policyholders had more favorable rate adjustments on average.

The poorest policyholders (under-$20,000 annual income) averaged rate increases of about 4% relative to the rates charged the $50,000 to $75,000 income group. Policyholders in the top category, $150,000 and up annually, averaged rate declines of about 4% relative to the $50,000 to $75,000 income group. These differences are adjusted to compare individuals of similar age.

Combination of Ethnicity and Income

Because ethnicity is associated with lower incomes among this firm's customers, the two effects cannot simply be added together to calculate, for example, the total average effect for policyholders who are both Native American and poor. The effects are slightly overlapping. So, on average, credit scoring raises the rates of poor Native Americans more than the rates of other low-income policyholders, but by less than the sum of 4 % and 15.5%.[15]

Zero Score

Ethnicity

After adjusting for the differences in the age composition of ethnic groups, there were no statistically

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12 As well as some driving record information not used in this analysis.

13 This analysis for effects on premium adjustments considered only those with non-zero credit scores.

14 Two different age adjustments were fitted, with nearly identical results.

15 The overlap reduces the effect to about 1.3 percentage points less than the sum of the separate effects. Low income Native American averaged about a 14.4% increase, relative to the low-income white population. The income effect declines slightly in the combined regression estimating both ethnicity and income. Credit scoring is estimated to have raised average rates for very low income Native Americans by about 18.2% relative to mid-income ($50-$75,000) white policyholders of similar age.

significant differences in the proportions of different ethnic groups who had a zero credit score.

Income

Credit scores of zero were more common among policyholders in the two lowest income categories. The overall probability of having a zero score was 28%. If a person had that average probability (28%) at middle and upper income levels, at low-income levels the same person would have a higher likelihood of a zero score:

- 48% if the group had annual incomes between $20,000 and $35,000, and
- 76% if the group had annual incomes between $20,000 and $35,000.

FIRM 3

Sample

The survey resulted in 978 responses. Among those contacted, 87.0% agreed to participate. This constituted 63.0% of those whom the interviewers tried to contact. This sample provided a margin of error of approximately ± 3 percent for a yes/no question.

Questions

Based on the findings from the first review, the principal questions were to determine the demographic pattern of both credit scores and the economic effects of those scores. Effects on policyholders with scores of "zero" due to inadequate credit history were identified as requiring separate analysis.

Structure

This firm uses credit scoring in two ways.

- First, in combination with other traditional underwriting factors, credit scores are used to assign applicants to either the standard risk pool or a higher-cost pool. Of the sample reached by phone interviewers, 362 had been placed in the non-standard higher rate pool, and 616 with the standard rate pool.
- Second, within each pool, a credit-based score is assigned, and this score is used as a starting point for determining a premium rate.

Data Provided

In addition to age, gender, zip code, and policy binder date, the insurer provided data on the insurance pool customers were placed in, and which of five "bands" or tiers their credit score placed them in.[16] There was no identification of individuals with insufficient credit files to generate a score. However, the insurer places such policyholders in the next-to-lowest band, with premiums higher than average, but lower than their maximum. Therefore, the analysis of premiums shifts for this firm examines two effects of credit scoring in combination. It analyses the combined effect of both the direct influence through credit scores and the indirect influence through classification of those with score of zero due to inadequate credit history.

Analyses

Assignment to Risk Pool

The first step, assignment to regular or high-cost pools, was evaluated for demographic patterns. However, this step involves not only credit information, but also other driving-related data. Therefore, we cannot conclude that any identified unequal impacts were caused by credit scoring. These impacts might result, partly or entirely, from the driving and insurance histories of the firm's customers, and not from their credit scores.

[16] Also included was information on type of insurance and final premium classification, which was not used in this analysis.

The effects of this combined credit and driving evaluation are quite marked demographically. People were more likely to have credit scores of zero if they were young, poorer, African American and/or Hispanic.[17] However, because this is not a purely credit-based determination, it cannot be concluded that this unequal impact results from credit scoring.

Premium Levels

The firm's premium rating process, which relies solely on credit scoring, was evaluated separately for each of the two insurance pools.

Lower Cost Pool- Ethnicity

Credit score information raised Hispanic policyholders' rates by an average of 4% of average premiums, relative to white policyholders of similar age.[18]

Lower Cost Pool- Income

There was no statistically significant connection between income and rate adjustments based on credit information, with or without adjustment for differences in age distribution.

High Cost Pool- Ethnicity

Credit score rating raised rates for two ethnic groups:

- For Blacks, by 5.6% of average premium, relative to whites of similar age,
- For Native Americans, by 8.6% of average premium, relative to whites of similar age.

High Cost Pool Income

There was no general correlation between income and credit score rate adjustments across all income levels. However, for those with incomes below $20,000, analyses consistently indicated rates about 2% above other income groups, even with adjustments for age and ethnicity. While this difference was consistent, it was not always statistically significant, depending on the technical specifics of the model.

High Cost Pool Overlap of Ethnicity and Income

In a combined analysis including ethnicity, age and income, the effects do not cancel each other out. So the results can be thought of as additive.[19]

See Appendix E for coefficients and regression details.

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[17] The proportion of individuals placed in the higher cost pool was 37%, or overall odds of about 3-to-5. If a white person of a particular age had this average probability (37%) of having a zero score, an otherwise similar black person had a 60% probability, and a Hispanic person, a 69% probability. If a person with a $65,000 annual income had the average probability of a zero score (37%), the average person of the same age with an income of $30,000 would have a 50% probability of a zero score.

[18] Small numbers of ethnic minorities, and the refusal of some of those few to provide income information, made it impossible to measure the possible interaction of ethnicity and income with any certainty.

[19] In fact, the estimated difference for African-Americans and Native Americans gets slightly larger in the combined analysis. The combined effect for poor African-Americans is 8.5%, and the combined effect for poor Native Americans is 11.3%. Paradoxically, while the factor for Native Americans both gets larger it also exceeds the statistical significance limit of .05, rising to .066. One of the consequences of the relatively low numbers of minority groups in the samples is that small changes in data or analytic models can change the results of statistical significance tests.

CONCLUSIONS

Based on these analyses, it is probable that credit-scoring impacts are not equally distributed across demographic groups. In almost every multivariate analysis, some groups were significantly associated with differential effects that have economic consequences. Although there were considerable differences among the models, it did not appear to be mere random variation.

The demographic effects varied significantly among the three insurers studied. Assuming that these three insurers are representative of insurers in general, substantial variation among insurers should be generally expected. Based on the variations found in these three firms, and on a limited literature review, variation in effects is likely due to differences in:

a. The credit scoring model used,
b. The population to which it is applied, and
c. The role credit scoring has in the insurer's underwriting and ratemaking processes.

Therefore, an overall conclusion that credit scoring generally does or does not have a particular consistent, quantifiable, unequal negative effect on certain demographic groups is premature. Possible negative effects will have to be directly evaluated using data on the outcomes for each insurer's practices and clientele, at least until there is more understanding of when and why particular unequal impacts result.

Classification based on credit score is not identical to classifying people based purely on demographic groupings. Rather, demographically unequal impacts appear to be significant side effects of credit scoring. No large demographic group has uniformly low credit scores. However, low credit scores may be much more common in some groups than others.

There are other potential negative consequences of credit scoring that are beyond this study's scope. Possible demographic inequality in decision about whom to insure is one such possibility. Erroneously identifying individuals for higher risks and premiums based on information unrelated to risks is another. Another possibility is inaccurate credit scores due to inaccurate information in the credit history systems.

SPECIFIC DEMOGRAPHIC PATTERNS

Age is Most Significant

In most analyses, older drivers had, on average, higher credit scores and lower probability of a zero credit score.[20] Because this pattern favors older drivers, and using youth as a risk factor for auto insurance has well-established legitimacy, age was considered mostly as an adjustment factor when analyzing the correlations of other characteristics with credit scores. Analyses for patterns in other demographic characteristics were done on an age-adjusted basis, except where testing demonstrated that age was not a significant factor.

Other Key Characteristics

Possible negative effects on ethnic minorities and low-income individuals were of particular concern in this study. The relationship of income and ethnicity to credit scores was much less consistent than the relationship between age and credit scores. It is possible that one implementation of credit scoring has significant effects in these areas, while another implementation does not. Larger samples and studies of additional insurers might clarify the patterns among these factors.

[20] There is some evidence that the age effect flattens at the lower end, and that those under 30 do not have worse credit associated scores and impacts than those aged 30-40, but this is complicated by age-related differences in the percentages not having a usable credit score.

1. Income

Income was the second most frequent factor of statistical significance, whether as a general tendency for credit scores to get better with rising income, or as a tendency for those in the lowest one or two income categories to have negative effects.[21] In some cases, lower income was also associated with higher probability of receiving a zero credit score due to lack of credit history.

2. Ethnicity

Ethnicity was also found to be a statistically significant factor in several cases. However, the relatively small numbers of ethnic minorities, and the number of refusals and unclassifiable survey responses made this very difficult to pin down. In general, the Asian/Pacific Islander individuals had credit effects more similar to whites than to other people of color. For non-Asian/Pacific Islander minorities, in those cases in which ethnicity differences were found to be significant, the differences were in the direction of higher costs for ethnic minorities.[22]

Other Factors Insignificant

Statistically significant results for gender, marital status and location were sufficiently infrequent that, if these three firms are a representative sample, less attention needs to be paid to possible patterns of negative effects for these groups. However, other reports indicate that some other insurers include credit information on additional drivers beyond the named policyholder in their credit scoring processes. It would be important to fully evaluate possible gender and marital status factors in studying insurers employing such practices.

[21] The lowest categories were "less than $20,000 per year" and "$20,000 to $35,000 per year."

[22] The consistency with which estimated effects for most minorities were in the direction of higher costs is one of the reasons this report recommends serious study and further investigation with larger samples. While estimated ethnicity effects often failed to pass tests for statistical significance, they were almost always in the direction of higher costs for minorities, except for Asian/Pacific Islanders.

APPENDIX A

TRANSUNION REASON CODES FOR NEGATIVE OR DEROGATORY CREDIT REPORTS

Excessive or unknown amount owed on accounts
Recent delinquency
Absence of revolving credit accounts
Too many accounts with balances
Too many finance company accounts
Too many recent credit checks
Too many new accounts
Proportion of revolving balances to revolving credit limits is too high or there are no revolving credit accounts
Excessive amount owed on revolving accounts
Insufficient length of revolving credit history
Delinquency date too recent (or date unknown)
Insufficient length of credit history
Delinquency
Recent derogatory public record or collection
Past due balances
Delinquency, derogatory public record or collection
Presence of collection accounts
Too many revolving accounts with balances
Date of last credit check too recent or unknown
Insufficient time since most recent account established
Unfavorable number of installment loan accounts
Too many installment loan accounts with outstanding balances
Insufficient time since most recent installment loan established
Too many accounts with high credit amounts
Proportion of loan balances to installment loan amounts is too high
Unfavorable number of real estate accounts
Too many new or existing finance company accounts
Prior installment loan delinquency or no installment loans present
Unfavorable percentage or open revolving accounts to all other accounts
Presence of delinquency, public record or collection
Delinquency on open revolving accounts
Finance company account opened recently
Unfavorable number of accounts
Unfavorable length of time since most recent retail account opened
Too many recently active finance company accounts
Unfavorable number of recently active accounts
Unfavorable number of revolving or open accounts
Unfavorable number of adverse public records

APPENDIX B

RANGE OF DEMOGRAPHICS IN THREE INSURERS' CLIENTELE*

Race		
	Low	**High**
Black	0.3%	3.3%
Hispanic	1.5%	7.4%
Caucasian	77.3%	94.3%
Asian/Pacific Islander	2.6%	9.1%
Native American	0.8%	1.5%
Multi-Racial	0.4%	1.1%
Other	0.4%	0.7%
Marital Status		
Single, Divorced, Separated	22.5%	44.9%
Married/Widowed	55.1%	77.5%
Gender		
Male	46.6%	66.0%
Female	34.0%	53.4%
Geography		
In Eastern Washington	13.0%	16.2%
In Metropolitan Statistical Area	76.0%	85.2%
Age Distribution		
Under 30	6.4%	30.1%
Between 30 & 40	11.4%	26.7%
Between 40 & 50	21.1%	28.3%
Between 50 & 60	13.7%	22.5%
Between 60 & 70	5.5%	17.2%
70 & Up	3.9%	17.2%
Annual Income		
Under $20,000	13.0%	23.9%
$20,000-$35,000	19.2%	27.1%
$35,000-$50,000	20.8%	23.1%
$50,000-$75,000	16.7%	21.3%
$75,000-$100,000	5.4%	11.5%
$100,000-$150,000	2.9%	7.6%
Over $150,000	2.3%	4.2%

*Estimated from Telephone Survey Samples

APPENDIX C

FIRM 1 REGRESSIONS FOR EFFECT ON CREDIT SCORE

Notes:

The dependent variable is credit score
Credit scores varied by 535 points, from lowest to highest

Ethnicity and Income

Notes:

Both Ethnicity and Income were not found to have statistically significant correlations with credit scores in this case.

Correlation with Age and other factors is shown in the regression described below.

	Linear Regression
Sample N	889
R Square	0.303
Adjusted R Square	0.300

	Unstandardized Coefficients	Standard Error Of Coefficient	Standardized Coefficients	T-Statistic	Range Of Values	Sig.
Age at Rating	**3.696**	0.199	0.529	18.620	22-98	**0.000**
Married Female	**15.790**	5.865	0.076	2.692	0-1	**0.007**
Eastern Washington	**-17.820**	7.747	-0.065	-2.300	0-1	**0.022**
Constant	518.528	11.064		46.864		

***Bolded entries in the first and last columns indicate statistically significant variables.**

Calculation of Change in score

<u>Notes:</u>

The Coefficients for Married Females and Eastern Washington residents are directly interpretable as:

- Plus 16 points on average for married women, after adjusting for age and proportion living in Eastern Washington

- Minus 18 points on average for Eastern Washington residents, after adjusting for age & proportion of married females

The results for married females apply to those cases in which they are the lead policyholder or "named insured".

Example Used in Footnote

	Coefficient (Change per one unit of the Factor)	Shift Measured in Years of Age difference	Credit Score Points
Age at Rating	**3.696**	10	37.0

FIRM 1 REGRESSION FOR HAVING A CREDIT SCORE OF ZERO DUE TO INADEQUATE CREDIT HISTORY

Ethnicity

Evidence That Correlations With Ethnicity Are Not Statistically Significant At This Sample Size

<u>Note:</u> The dependent variable is the categorical outcome of having a credit score of zero. Coding 1= having a score of zero.

	Logistic Regression
Sample N	917
Cox & Snell R Square	0.015
Nagelkerke R Square	0.053

	Raw Coefficient	Standard Error	Wald Statistic	Range Of Values	Significance	Exponentiated Coefficient
Age	-0.163	0.061	7.117	22-98	**0.008**	**0.850**
Age Squared	0.002	0.001	8.949	484-9604	**0.003**	**1.002**
African American	-4.597	34.879	0.017	0-1	0.895	0.010
Hispanic	-4.997	16.591	0.091	0-1	0.763	0.007
Asian/Pacific Islander	0.917	0.775	1.400	0-1	0.237	2.502
Native American	-4.830	30.055	0.026	0-1	0.872	0.008
Multi-Ethnic	-4.692	21.321	0.048	0-1	0.826	0.009
Constant	0.471	1.643	0.082	1.000	0.775	1.601

***Bolded entries in the first and last columns indicate statistically significant variables.**

Income

Note: The dependent variable is the categorical outcome of having a credit score of zero. Coding 1= having a score of zero.

	Logistic Regression
Sample N	847
Cox & Snell R Square	0.026
Nagelkerke R Square	0.094

	Raw Coefficient	Standard Error	Wald Statistic	Range Of Values	Significance	Exponentiated Coefficient
Income less than $20,000	1.865	0.367	25.900	0-1	**0.000**	**6.458**
Constant	-3.690	0.239	239.195		0.000	0.025

***Bolded entries in the first and last columns indicate statistically significant variables.**

Calculation Of Odds And Probability Shifts For Example In Text

	Typical Probability	Probability Expressed As Odds Ratio Relative To 1	Exponentiated Coefficient	Odds Ratio With Characteristic (Relative To 1)	New Odds Ratio Expressed As Probability
Income less than $20,000	0.04	0.042	6.458	0.269	21.2%

APPENDIX D

FIRM 2 REGRESSIONS FOR PREMIUM SHIFT

Ethnicity

Notes:

The dependent variable is percentage reduction in premium down from maximum rates.

Credit based rate adjustments ranged to 32 % below maximum, which translates as from 17% below average premium to 33% above average premium.

	Linear Regression
Sample N	767
R Square	0.058
Adjusted R Square	0.055

	Unstandardized Coefficients	Standard Error of Coefficient	Standardized Coefficients	T-statistic	Range of Values	Sig.
African American	-3.755	3.127	-0.042	-1.201	0-1	0.230
Hispanic	-2.688	1.999	-0.047	-1.345	0-1	0.179
Asian/Pacific Islander	**4.110**	1.914	0.075	2.147	0-1	**0.032**
Native American	**-11.827**	3.133	-0.131	-3.775	0-1	**0.000**
Age at Rating	**0.250**	0.039	0.273	6.367	16-91	**0.000**
Age less than 30	**2.967**	1.414	0.090	2.098	0-1	**0.036**
Constant	**14.598**	1.890		7.722		**0.000**

***Bolded entries in the first and last columns indicate statistically significant variables.**

Calculation of Change in Rates

Note: Each percentage point below maximum translates to 1.333 percentage points relative to the average rate, which is 75% of the maximum.

	Coefficient	Conversion Factor From Percent Of Maximum To Percent Of Average	Change In Premium Expressed As Percent Of Average
Asian/Pacific Islander	**4.110**	1.333	-5.5%
Native American	**-11.827**	1.333	15.8%

Income

First Version of Age Adjustment

	Linear Regression
Sample N	767
R Square	0.072
Adjusted R Square	0.068

	Unstandardized Coefficients	Standard Error Of Coefficient	Standardized Coefficients	T-Statistic	Range Of Values	Sig.
Income	**0.966**	0.283	0.121	3.419	1-7	**0.001**
Age at Rating	**0.263**	0.039	0.288	6.679	16-91	**0.000**
Age less than 30	**3.710**	1.438	0.113	2.581	0-1	**0.010**
Constant	10.923	2.106		5.187		0.000

***Bolded entries in the first and last columns indicate statistically significant variables.**

Calculation of Change in Rates

Note: Each percentage point below maximum translates to 1.333 percentage points relative to the average rate, which is 75% of the maximum.

	Coefficient (Change Per One Unit Of The Factor)	Shift As Measured In Number Of Income Groups		Conversion Factor From Percent Of Maximum To Percent Of Average	Change In Premium Expressed As Percent Of Average
Income	**0.966**	3.000	2.898	1.333	-3.9%

Second Version of Age Adjustment

	Linear Regression
Sample N	767
R Square	0.076
Adjusted R Square	0.072

	Unstandardized Coefficients	Standard Error Of Coefficient	Standardized Coefficients	T-Statistic	Range Of Values	Sig.
Income	**1.017**	0.283	0.127	3.590	1-7	**0.000**
Age at Rating-Squared	**0.006**	0.002	0.619	3.190	256->8281	**0.001**
Age at Rating	**-0.354**	0.178	-0.387	-1.992	16-91	**0.047**
Constant	25.822	3.922		6.584		0.000

***Bolded entries in the first and last columns indicate statistically significant variables.**

Calculation of Change in Rates

Note: Each percentage point below maximum translates to 1.333 percentage points relative to the average rate, which is 75% of the maximum.

	Coefficient (Change Per One Unit Of The Factor)	Shift As Measured In Number Of Income Groups		Conversion Factor From Percent Of Maximum To Percent Of Average	Change In Premium Expressed As Percent Of Average
Income	**1.017**	3.000	3.050	1.333	-4.1%

Example of Combined Regression for Both Income and Ethnicity, Age-Adjusted

	Linear Regression
Sample N	767
R Square	0.101
Adjusted R Square	0.093

	Unstandardized Coefficients	Standard Error of Coefficient	Standardized Coefficients	T-statistic	Range of Values	Sig.
Income	**0.944**	0.283	0.118	3.337		**0.001**
Age at Rating-Squared	**0.006**	0.002	0.620	3.228		**0.001**
Age at Rating	**-0.361**	0.176	-0.395	-2.050		**0.041**
African American	-3.783	3.101	-0.042	-1.220		0.223
Hispanic	-2.244	1.983	-0.039	-1.132		0.258
Asian/Pacific Islander	**4.550**	1.903	0.083	2.390		**0.017**
Native American	**-10.798**	3.127	-0.120	-3.453		**0.001**
Constant	26.439	3.912		6.758		0.000

***Bolded entries in the first and last columns indicate statistically significant variables.**

Calculation of Change in Rates

Note: Each percentage point below maximum translates to 1.333 percentage points relative to the average rate, which is 75% of the maximum.

	Coefficient (Change Per One Unit Of The Factor)	Shift As Measured In Number Of Income Groups		Conversion Factor From Percent Of Maximum To Percent Of Average	Change In Premium Expressed As Percent Of Average
Income	**0.944**	3.000	2.831	1.333	-3.8%

	Coefficient	Conversion Factor From Percent Of Maximum To Percent Of Average	Change In Premium Expressed As Percent Of Average
Asian/Pacific Islander	**4.550**	1.333	6.1%
Native American	**-10.798**	1.333	-14.4%

FIRM 2 REGRESSION FOR HAVING A CREDIT SCORE OF ZERO DUE TO INADEQUATE CREDIT HISTORY

Ethnicity

Evidence That Correlations With Ethnicity Are Not Statistically Significant At This Sample Size

Note: The dependent variable is the categorical outcome of having a credit score of zero. Coding 1= having a score of zero.

	Logistic Regression
Sample N	957
Cox & Snell R Square	0.020
Nagelkerke R Square	0.039

	Raw Coefficient	Standard Error	Wald Statistic	Range Of Values	Significance	Exponentiated Coefficient
Age less than 30	0.740	0.240	9.472	0-1	**0.002**	**2.096**
African American	0.897	0.582	2.378	0-1	0.123	2.453
Hispanic	0.675	0.376	3.213	0-1	0.073	1.963
Asian/Pacific Islander	0.520	0.389	1.787	0-1	0.181	1.682
Native American	-5.194	9.385	0.306	0-1	0.580	0.006
Multi-Ethnic	-0.036	1.074	0.001	0-1	0.973	0.964
Constant	-2.247	0.125	321.619		0.000	0.106

Income

Note: The dependent variable is the categorical outcome of having a credit score of zero. Coding 1= having a score of zero.

	Logistic Regression
Sample N	883
Cox & Snell R Square	0.067
Nagelkerke R Square	0.129

	Raw Coefficient	Standard Error	Wald statistic	Range of Values	Significance	Exponentiated Coefficient
Income Less Than $20,000	2.073	0.291	50.923	0-1	**0.000**	**7.952**
Income $20,000 To $35,000	0.881	0.321	7.534	0-1	**0.006**	**2.413**
Income $75,000 To $100,000	0.926	0.468	3.921	0-1	**0.048**	**2.524**
Constant	-3.023	0.241	156.876		0.000	0.049

***Bolded entries in the last two columns indicate statistically significant variables.**

Notes:

The statistically significant results for the $75,000-$100,000 income category are anomalous, and no explanation has been suggested.

Age adjustment was not significant in this particular model: in other versions, an adjustment for age under 30 was significant, but inclusion of this adjustment does not substantially change the income effects.

	Typical Probability	Probability Expressed As Odds Ratio Relative To 1	Exponentiated Coefficient	Odds Ratio With Characteristic (Relative To 1)	New Odds Ratio Expressed As Probability
Income Less Than $20,000	28.0%	0.389	7.952	3.092	75.6%
Income $20,000 To $35,000	28.0%	0.389	2.413	0.938	48.4%

APPENDIX E

FIRM 3 REGRESSION FOR ASSIGNMENT TO HIGH OR LOW RISK INSURANCE POOL

Ethnicity and Income

CAUTION: Risk pool assignment is based on a combination of credit factors and traditional auto insurance factors such as driving and insurance history. The outcomes analyzed in this regression may partly or entirely result from factors other than credit history.

Combined Ethnicity and Income Regression, Age-Adjusted

Note: The dependent variable is the categorical outcome of being placed in the high risk/high cost pool. Coding 1= hi pool.

	Logistic Regression
Sample N	862
Cox & Snell R Square	0.111
Nagelkerke R Square	0.151

	Raw Coefficient	Standard Error	Wald Statistic	Range of Values	Significance	Exponentiated Coefficient
African American	0.931	0.409	5.181	0-1	**0.023**	**2.537**
Hispanic	1.316	0.296	19.810	0-1	**0.000**	**3.728**
Asian/Pacific Islander	-0.155	0.265	0.341	0-1	0.559	0.856
Native American	-0.527	0.690	0.584	0-1	0.445	0.590
Multi-Ethnic	-0.087	0.670	0.017	0-1	0.896	0.916
Age at Rating	-0.027	0.005	25.904	18-86	**0.000**	**0.974**
Income Group	-0.268	0.054	24.646	0-1	**0.000**	**0.765**
Constant	1.168	0.243	23.137		0.000	3.216

Bolded entries in the last two columns indicate statistically significant variables.

Calculation Of Odds And Probability Shifts For Examples

<u>Notes:</u>

Odds ratios for ethnicity are relative to odds for whites.

Odds ratios for income apply to shifting between any two income levels up or down the income scale. The regression coefficients are expressed for movement up the scale. For movement down the income scale, exponentiated coefficients invert (1 divided by the exponentiated coefficient).

	Typical Probability	Probability Expressed As Odds Ratio Relative To 1	Exponentiated Coefficient	Odds Ratio With Characteristic (Relative To 1)	New Odds Ratio Expressed As Probability
African American	37.0%	0.587	2.537	1.490	59.8%
Hispanic	37.0%	0.587	3.728	2.190	68.6%

	Typical Probability	Probability Expressed As Odds Ratio Relative To 1	Exponentiated Coefficient	Change Measured In Number Of Income Categories	Exponentiated Coefficient For That Number Of Units Of Change	Odds Ratio After Shift In Characteristic (Relative To 1)	New Odds Ratio Expressed As Probability
Income-Upwards	37.0%	0.587	0.765	2.000	0.585	0.343	25.6%
Income-Downwards	37.0%	0.587	1.308	2.000	1.711	1.005	50.1%

FIRM 3 REGRESSION FOR SCORE IN LOW RISK INSURANCE POOL

Ethnicity

Note: The dependent variable is rating tiers 1 through five. Tier number five has the highest premiums.

	Linear Regression
Sample N	579
R Square	0.096
Adjusted R Square	0.088

	Unstandardized Coefficients	Standard Error of Coefficient	Standardized Coefficients	T-statistic	Range of Values	Sig.
African American	0.454	0.298	0.061	1.523	0-1	0.128
Hispanic	**0.539**	0.246	0.088	2.195	0-1	**0.029**
Asian/Pacific Islander	-0.110	0.157	-0.028	-0.701	0-1	0.484
Native American	0.271	0.370	0.029	0.731	0-1	0.465
Age at Rating	**-0.021**	0.003	-0.288	-7.169	19-86	**0.000**
Constant	3.296	0.139		23.710		0.000

***Bolded entries in the last two columns indicate statistically significant variables.**

Calculation of Change in Rates

Note: For each rating tier, premiums rise by about 6% of maximum rates, or about 7.3% of average rates

	Coefficient	Premium Increase Per Tier	Percentage Premium Increase
Hispanic	0.539	0.073	3.9%

Income

There are no significant results correlating income with tier classification in the risk pool.

FIRM 3 REGRESSION FOR SCORE IN HIGH RISK INSURANCE POOL

Ethnicity

Note: The dependent variable is rating tiers one through five. Tier number five has the highest premiums.

	Linear Regression
Sample N	341
R Square	0.070
Adjusted R Square	0.056

	Unstandardized Coefficients	Standard Error Of Coefficient	Standardized Coefficients	T-Statistic	Range Of Values	Sig.
African American	**0.773**	0.291	0.141	2.655	0-1	**0.008**
Hispanic	0.121	0.178	0.036	0.678	0-1	0.498
Asian/Pacific Islander	0.000	0.226	0.000	0.002	0-1	0.998
Native American	**1.170**	0.570	0.109	2.051	0-1	**0.041**
Age at Rating	**-0.016**	0.004	-0.189	-3.539	18-84	**0.000**
Constant	2.994	0.178		16.780		0.000

***Bolded entries in the last two columns indicate statistically significant variables.**

Calculation of Change in Rates

Note: For each rating tier, premiums rise by about 6% of maximum rates, or about 7.3% of average rates

	Coefficient	Premium Increase Per Tier	Percentage Premium Increase
African American	0.772660487	0.073	5.64%
Native American	1.170093545	0.073	8.54%

Ethnicity and Income Combined

Note: The dependent variable is rating tiers one through five. Tier number five has the highest premiums.

	Linear Regression
Sample N	325
R Square	0.080
Adjusted R Square	0.063

	Unstandardized Coefficients	Standard Error Of Coefficient	Standardized Coefficients	T-Statistic	Range Of Values	Sig.
African American	**0.850**	0.302	0.153	2.814	0-1	**0.005**
Hispanic	0.075	0.185	0.022	0.407	0-1	0.684
Asian/Pacific Islander	-0.035	0.232	-0.008	-0.152	0-1	0.879
Native American	1.218	0.660	0.100	1.847	0-1	0.066
Age at Rating	**-0.015**	0.005	-0.177	-3.201	18-84	**0.002**
Income less than $20,000	**0.289**	0.139	0.115	2.082	0-1	**0.038**
Constant	2.877	0.197		14.603		0.000

***Bolded entries in the last two columns indicate statistically significant variables.**

Calculation Of Change In Rates For Examples Used In The Report

Note: For each rating tier, premiums rise by about 6% of maximum rates, or about 7.3% of average rates

	Coefficient	Premium Increase Per Tier	Percentage Premium Increase
African American	0.850	0.073	6.20%
Native American	1.218	0.073	8.89%
Income Less Than $20,000	0.289244437	0.073	2.11%

APPENDIX F

GLOSSARY OF TERMS

Overall Terms and Definitions

Constant – Both linear and logistic regressions include statistics for "constant" factors. They are include here for sake of completeness in description of the regressions, and not because they have policy implications. They can be thought of as the score or probability that is estimated for the starting or reference combination of characteristics, the one to which the shifts indicated by all the other factors are relative. Constant terms are required in order to calculate the estimated probability for a specific combination of characteristics.

Dependent Variable – The dependent variable is the outcome for which correlated factors are to be identified and quantified in the regression model.

Income Group – In all of the surveys, income information was collected by the categories below. Although these categories are not of perfectly equal size, it was treated as a linear variable in analysis. Use of both Age and Age-Squared factors should have permitted the regression to correctly identify patterns of correlation with income in spite of the fact that the group intervals widened as income rose.

1 Under $20,000
2 $20,000 to less than $35,000
3 $35,000 to less than $50,000
4 $50,000 to less than $75,000
5 $75,000 to less than $100,000
6 $100,000 to less than $150,000
7 $150,000 and above

Sample N – The number of policyholder records that were usable for that analysis: they belonged to the group being analyzed and had no missing values for the variables used.

Significance – The probability that the pattern represented by the coefficient for this factor really doesn't exist in the overall population, but is due to random chance producing a sample that has a pattern. This report used the criterion that only results with probabilities of error of 5% or less were considered statistically significant. This corresponds to a value of .05 in the Significance columns of the coefficient tables.

Standard Error – The interval plus or minus around any estimate which defines the area we are 95% confident includes the true value.

Linear Regression Terms

Linear Regression – This is a method for quantifying the simultaneous strength of association of several factors with an outcome which can be quantified on a numerical scale. The most common linear method, Ordinary Least Squares (OLS), was used.

R Square, Adjusted R Square – These are the two standard measures of the exp lanatory power of a Linear Regression. They both are on a zero-to-one scale, and give different mathematical approximations of what percentage of the variance in the outcome the model explains. In comparing the power or accuracy of regressions, R squares from different formulas should not be contrasted with each other: compare unadjusted scores to unadjusted scores, and adjusted scores to adjusted scores.

Standardized Coefficient – This is a measure of the overall significance of a factor in the model. Neither significance statistics nor the magnitude of an unstandardized coefficient are unambiguous measures of the significance of a factor in the explanatory power of a regression. For example, a factor may have a large effect (coefficient) and be highly significant, but have little overall significance because it is present in only a few cases, and therefore contributes only a small amount to overall accuracy.

T-Statistic – Another standard measure of statistical significance.

Unstandardized Coefficients – This expresses the strength of the correlation, scaled so that it corresponds to the scale on which the factor was measured. It can be directly multiplied times units of the factor in order to estimate how the dependent variable varies with a given variation in the factor. For categorical factors, such as being male, the unstandardized coefficient is the average difference the factor is associated with, adjusted for other factors in the model.

Logistic Regression Terms

Exponentiated Coefficient – Exponentiated logistic coefficients represent the shift in odds ratios correlated with a one-unit change in a correlated factor. To apply an exponentiated coefficient, express the probability of the outcome in the absence of that characteristic in terms of the odds in favor of the outcome, and multiply the numerator of the odds ratio to calculate how that factor shifts odds.

A shift by more than one unit in one of these factors is not additive, but has a power form. For example, if the exponentiated coefficient for age is 0.9, the coefficient for being three years older is 0.9 cubed, or 0.9 x 0.9 x 0.9.

As an example, take a case in which the regression sets a variable "female=1" for being female, so lacking that factor indicates being male. If the odds that males will have a credit score of zero are 1-to-4, and the exponentiated coefficient for females is 0.5, then the odds for females are .5-to-4, or 1-to-8.

Any probability that can be expressed as a percentage, can also be expressed as an odds ratio: 75% is 3-to1, 50% 1-to-1, and 10% is 1-to-9 in favor. Note that these are odds, or odds ratios, not probabilities or proportions. Odds of 1-to-4 is "one out of five" or a 20% probability. Odds of 1-to-8 is "one out of nine" or an 11.1% probability. Odds that a coin will land heads-up are 1-to-1, and odds that a person was born on a Monday are 1-to-6.

Raw Coefficient – These are the mathematical coefficients as generated by the regression model. They have a direct mathematical relationship to the Exponentiated Coefficients, as described above.

Logistic Regression – This is a method for quantifying the simultaneous strength of association of multiple factors with an outcome that is "categorical" – that is, it cannot be quantified on a numerical scale. Categorical outcomes are either true or false, there are no intermediate values. The strength of a factor's association with a categorical outcome is described in terms of how it is associated with the probability or likelihood of that outcome.

Nagelkerke R Square, Cox & Snell R Square – These are two standard measures of the explanatory power of a Logistic regression. They both are on a zero-to-one scale, and give different mathematical approximations of what percentage of the variance in the outcome the model explains. The "percentage of variance explained" is not as straightforward a concept in dealing with categorical dependent variables. In comparing the power or accuracy of regressions, R squares from different formulas should not be contrasted with each other: compare a Nagelkerke with a Nagelkerke, and a Cox & Snell score with a Cox & Snell score.

Wald Statistic – This is a measure of the overall strength of a factor in the model. Neither significance statistics nor the magnitude of a raw coefficient are unambiguous measures of the significance of a factor in the overall power of a regression. For example, a factor may have a large effect (coefficient) and be highly significant, but have little overall significance because it is present in only a few cases, and therefore improves overall accuracy only a small amount.

APPENDIX G

TELEPHONE SURVEY – LONG VERSION

Q.1 Record Source : Which list is this from ?

	(7)
Cancelled Policy Holders ..	1
Current Policy Holders	2

Q.2 Hello. I'm calling on behalf of the Office of the State Insurance Commissioner. I want to assure you this is not a sales call. May I please speak with _________________ (the policy holder)?

	(8)
Yes ..	1
No	2

Q.3 Am I speaking with the Policy Holder, Someone who can speak for the policy holder, or neither ?

	(9)
Policy holder	1
Someone who can speak for the policyholder ..	2
Neither	3

[IF THE ANSWER TO QUESTION 3 IS 1 OR 2, THEN SKIP TO QUESTION 9]

Q.4 Can I speak with the policyholder ?

	(10)
Yes ..	1
No	2

[IF THE ANSWER TO QUESTION 4 IS 1, THEN SKIP TO QUESTION 9]

Q.5 (If No) "Is someone else available who could speak for the policyholder about his/her/your auto insurance?

	(11)
Yes ..	1
No	2

[IF THE ANSWER TO QUESTION 5 IS 2-3, THEN SKIP TO QUESTION 35]

Q.6 (If Yes) -- Who is that person?

____ (5-105)

Q.7 Can we speak to them or should we call back at another time?

(12)
Speak 1
Call Back .. 2

[IF THE ANSWER TO QUESTION 7 IS NOT 2, THEN SKIP TO QUESTION 9]

Q.8 When would be a good time to call back ?

____ (106-206)

[IF THE ANSWER TO QUESTION 7 IS 2, THEN SKIP TO QUESTION 35]

Q.9 The Insurance Commissioner recently sent a letter asking for your help in investigating auto insurance cancellations. I'd like to ask you several questions that will help him determine if certain practices should be prohibited. This will take no more than 7 minutes of your time. Your answers will be kept strictly confidential, and combined with other responses to protect your identity. Your responses will not be revealed to your insurance company or to anyone else. (record call disposition)

	(5-6)
Call Back-Appointment	01
Call Back N0-appointment ..	02
Respondent not available	03
Refusal to participate	04
--	05
Communication Barrier	06
Continue Survey	07
--	08
--	09
--	10

[IF THE ANSWER TO QUESTION 9 IS NOT 7, THEN SKIP TO QUESTION 35]

Q.10 (Record gender - ask if respondent is not policyholder or name is ambiguous)

(13)
Male 1
Female .. 2

[IF THE ANSWER TO QUESTION 1 IS NOT 1, THEN SKIP TO QUESTION 12]

Q.11 Firm 1 reported that they cancelled or declined to renew your auto insurance within the last year, is this correct?

(14)
Yes 1
No 2
Don't know ..3

[IF THE ANSWER IS 2-3, THEN SKIP TO QUESTION 27]

[IF THE ANSWER TO QUESTION 1 IS NOT 2, THEN SKIP TO QUESTION 13]

Q.12 Firm 1 reported that you have auto insurance with them, is this correct?

(15)
Yes 1
No 2
Don't know ..3

[IF THE ANSWER IS NOT 1, THEN SKIP TO QUESTION 35]

[IF THE ANSWER TO QUESTION 1 IS 2, THEN SKIP TO QUESTION 27]

Q.13 Did you receive a letter from the insurance company explaining why you (they) were denied auto insurance?

(16)
Yes 1
No 2
Don't know ..3

[IF THE ANSWER TO QUESTION 13 IS NOT 1, THEN SKIP TO QUESTION 15]

Q.14 Did the letter adequately explain why you (they) were denied auto insurance?

(17)
Yes 1
No 2
Don't know ..3

Q.15 On a scale of 1 to 10 (with 1 being not difficult at all and 10 being extremely difficult) how difficult has it been for you (or policyholder) to find new auto insurance coverage?

Difficulty ________ (42-43)

Q.16 How many insurance companies did you (or policyholder) have to contact? __________

Number of companies (0 for Don't Know)._______ (19-20)

Q.17 Were you (or policyholder) able to obtain replacement coverage?

(21)
Yes 1
No 2
Waiting to hear if approved .. 3
Don't know 4

[IF THE ANSWER IS 3, THEN SKIP TO QUESTION 25]

Q.18 Was there a period of time between the expiration of your former policy and the replacement policy?

(22)
Yes 1
No 2
Don't know ..3

Q.19 How much more or less do you (or policyholder) pay per month for this coverage compared to the previous coverage? (INTERVIEWER - IF RESPONDENT GIVES A 6 MONTH OR ANNUAL PREMIUM AMOUNT, CONVERT TO MONTHLY AMOUN

Amount (negative f or less, 0 for same, blank for don't__________ (23-27)

Q.20 Is the auto insurance coverage on the new policy different from the coverage on the old policy?

(34)
Yes 1
No 2
Don't know ..3

Q.21 Does the new policy cover more drivers, fewer drivers, or the same number of drivers as the old policy?

(35)
Fewer 1
Same 2
More 3
Don't know ..4

Q.22 Does the new policy cover more, fewer or the same number of vehicles?

(36)
Fewer 1
Same 2
More 3
Don't know ..4

Q.23 Is the deductible on the new policy lower, higher, or the same?

(37)
Lower 1
Same 2
Higher 3
Don't know ..4

Q.24 Is the collision coverage the same on the new policy?

(38)
Yes 1
No 2
Didn't have collision on previous policy...3
Don't know 4

Q.25 Can you tell me what company you (or policyholder) are now insured with? (Do Not Read, check the one that applies)

(40-41)
Not currently insured 01
Pemco 02
Safeco 03
Allstate 04
State Farm 05

Geico	06
Progessive	07
American Express	08
Nations	09
Other (please specify)	10
Insure Quest	11
Oregon Mutual	12
Financial Indemity	13
Farmers	14
Hartford	15
Nationwide	16
Uniguard	17
National	18
Diaryland	19
Valley Insurance	20
Grange	21
Allied	22
Amica	23
Metropolitian Life	24
GMAC	25
CNA	26
Unitrin	27
Omni	28
Quest	29
United	30
Kemper	31
American Commerce	32
Windsor	33
USAA	34
AIG	35
Lunatrend	36
QBE Insurance Group	37
AAA	38
Owsley Insurance	39
Viking	40
Simon Financial Group	41
JBR	42
Encompass	43
General	44
Vancouver Insurance	45
Horace Mann	46
County Company Insurance ..	47
E Surance	48
Mutual Of Omaha	49
Interquest	50
DON'T KNOW/REFUSED.......	99

Q.26 OTHER : Can you tell me what company you (or policyholder) are now insured with? (Do Not Read, check the one that applies)

____ (207-307)

Q.27 Can you please tell me if you (or policyholder) are...

	(60)
Married	1
Single	2
Divorced	3
Widowed	4
Seperated	5
Other (please specify) ..	6

Q.28 OTHER: Can you please tell me if you (or policyholder) are...

____ (308-358)

Q.29 Is your (or policyholder's) age:

	(61)
Under 16	1
16 - 24	2
25 - 34	3
35 - 44	4
45 - 54	5
55 - 64	6
65 - 74	7
75 and older ..	8
Refuse	9

Q.30 How do (does) you (or policyholder) identify your (policyholder's) race or ethnicity: (INTERVIEWER - DO NOT READ THE LIST. ACCEPT MULTIPLE ANSWERS)

	(64-83)
Black/ African American	01
Spanish/ Hispanic/Latino	02
Mexican, Mexican Am., Chicano, Puerto Rican, Cuban ..	03
Other Spanish/ Hispanic/Latino (Please specify)	04
White/Caucasian	05
American Indian or Alaska Native (Please specify)	06
Native Hawaiian, Guamanian or Chamorro, Samoan	07
Other Pacific Islander (Please specify)	08
Asian Indian	09
Chinese	10
Filipino	11
Japanese	12
Korean	13
Vietnamese	14
Other Asian (Please specify).	15
Other race (Please specify)	16
Multiracial	17
Refuse	18
Native American	20

Q.31 OTHER : How do (does) you (or policyholder) identify your (policyholder's) race or ethnicity:

____ (359-409)

Q.32 Which of the following income categories applies to your (or policyholder's) individual total annual income for 2000?

	(84)
Under $20,000	1
$20,000 - $34,999	2
$35,000 - $49,999	3
$50,000 - $74,999	4
$75,000 - $99,999	5
$100,000-149,999	6
$150,000 and above ..	7
Refuse	8

Q.33 Would you like to receive a report from the Insurance Commissioner about the outcome of our research?

(85)
Yes ..1
No 2

[IF THE ANSWER TO QUESTION 33 IS NOT 1, THEN SKIP TO QUESTION 35]

Q.34 Name and Address

____ (410-510)

Q.35 That is all the questions I have for you. Thank you for taking the time to participate in this research. (Interviewer ID#)

APPENDIX H

TELEPHONE SURVEY – SHORT VERSION

Q.1 Record Source : Which list is this from ?

	(7)
Cancelled Policy Holders	..1
Current Policy Holders	2

Q.2 Hello. I'm calling on behalf of the Office of the State Insurance Commissioner. I want to assure you this is not a sales call. May I please speak with ________________ (the policy holder)?

	(8)
Yes	..1
No	2

Q.3 Am I speaking with the Policy Holder, Someone who can speak for the policy holder, or neither ?

	(9)
Policy holder	1
Someone who can speak for the policyholder ..	2
Neither	3

[IF THE ANSWER TO QUESTION 3 IS 1 OR 2, THEN SKIP TO QUESTION 9]

Q.4 Can I speak with the policyholder ?

	(10)
Yes	..1
No	2

[IF THE ANSWER TO QUESTION 4 IS 1, THEN SKIP TO QUESTION 9]

Q.5 (If No) "Is someone else available who could speak for the policyholder about his/her/your auto insurance?

	(11)
Yes	..1
No	2

[IF THE ANSWER TO QUESTION 5 IS 2-3, THEN SKIP TO QUESTION 35]

Q.6 (If Yes) -- Who is that person?

____ (5-105)

Q.7 Can we speak to them or should we call back at another time?

(12)
Speak 1
Call Back .. 2

[IF THE ANSWER TO QUESTION 7 IS NOT 2, THEN SKIP TO QUESTION 9]

Q.8 When would be a good time to call back ?

____ (106-206)

[IF THE ANSWER TO QUESTION 7 IS 2, THEN SKIP TO QUESTION 35]

Q.9 The Insurance Commissioner recently sent a letter asking for your help in investigating auto insurance cancellations. I'd like to ask you several questions that will help him determine if certain practices should be prohibited. This will take no more than 7 minutes of your time. Your answers will be kept strictly confidential, and combined with other responses to protect your identity. Your responses will not be revealed to your insurance company or to anyone else. (record call disposition)

	(5-6)
Call Back-Appointment	01
Call Back N0-appointment ..	02
Respondent not available	03
Refusal to participate	04
--	05
Communication Barrier	06
Continue Survey	07
--	08
--	09
--	10

[IF THE ANSWER TO QUESTION 9 IS NOT 7, THEN SKIP TO QUESTION 35]

Q.10 (Record gender - ask if respondent is not policyholder or name is ambiguos)

(13)
Male 1
Female .. 2

[IF THE ANSWER TO QUESTION 1 IS NOT 1, THEN SKIP TO QUESTION 12]

Q.11 Can you please tell me if you (or policyholder) are...

(60)
Married 1
Single 2
Divorced 3
Widowed 4
Seperated 5
Other (please specify) ..6

Q.12 OTHER: Can you please tell me if you (or policyholder) are...

____ (308-358)

Q.13 Is your (or policyholder's) age:

	(61)
Under 16	1
16 - 24	2
25 - 34	3
35 - 44	4
45 - 54	5
55 - 64	6
65 - 74	7
75 and older	8
Refuse	9

Q.14 How do (does) you (or policyholder) identify your (policyholder's) race or ethnicity: (INTERVIEWER - DO NOT READ THE LIST. ACCEPT MULTIPLE ANSWERS)

	(64-83)
Black/ African American	01
Spanish/ Hispanic/Latino	02
Mexican, Mexican Am., Chicano, Puerto Rican, Cuban	03
Other Spanish/ Hispanic/Latino (Please specify)	04
White/Caucasian	05
American Indian or Alaska Native (Please specify)	06
Native Hawaiian, Guamanian or Chamorro, Samoan	07
Other Pacific Islander (Please specify)	08
Asian Indian	09
Chinese	10
Filipino	11
Japanese	12
Korean	13
Vietnamese	14
Other Asian (Please specify).	15
Other race (Please specify)	16
Multiracial	17
Refuse	18
Native American	20

Q.15 OTHER : How do (does) you (or policyholder) identify your (policyholder's) race or ethnicity:

____ (359-409)

Q.16 Which of the following income categories applies to your (or policyholder's) individual total annual income for 2000?

	(84)
Under $20,000	1
$20,000 - $34,999	2
$35,000 - $49,999	3
$50,000 - $74,999	4
$75,000 - $99,999	5
$100,000-149,999	6
$150,000 and above	7
Refuse	8

Q.17 Would you like to receive a report from the Insurance Commissioner about the outcome of our research?

(85)
Yes ..1
No 2

[IF THE ANSWER TO QUESTION 33 IS NOT 1, THEN SKIP TO QUESTION 35]

Q.18 Name and Address

______________________________ (410-510)

Q.19 That is all the questions I have for you. Thank you for taking the time to participate in this research. (Interviewer ID#)